Automatic Identification of Behavior Patterns in Mild Cognitive Impairments and Alzheimer's Disease Based on Activities of Daily Living

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Abstract. The growing number of older adults worldwide places high pressure on identifying dementia at its earliest stages so that early management and intervention strategies could be planned. In this study, we proposed a machine learning based method for automatic identification of behavioral patterns of people with mild cognitive impairments and Alzheimer's disease through the analysis of data related to their activities of daily living collected in two smart homes environments. Our method employs first a feature selection technique to extract relevant features for classification and reduce the dimensionality of the data. Then, the output of the feature selection is fed into a random forest classifier for classification. We recruited three groups of participants in our study: healthy older adults, older adults with mild cognitive impairments and older adults with Alzheimer's disease. We conducted extensive experiments to validate our proposed method. We experimentally showed that our method outperforms state-of-the-art machine learning algorithms.

1 Introduction and Related Work

New research has shown that early signs of dementia can be detected 10 years before the formal diagnosis is made [18]. At this time, individuals start showing dysfunctions in complex activities of daily living (ADL) such as managing one's finances [18, 4, 2, 21]. However, differentiating these early signs of dementia from normal cognitive aging requires an in-depth knowledge of the subtle differences observed in ADL function in these two populations. Considering the expected increase in prevalence of dementia in the coming years worldwide, it is urgent that we refine measures used to document ADL changes in the aging population so that appropriate prevention strategies can be put into place to minimize the repercussions of these diseases on the individuals and their family.

ADL dysfunctions in aging have been generally measured with questionnaires and performance-based assessments that generally fail to capture the person's actual performance and difficulties in everyday life [12, 11, 6, 3]. An alternative and innovative approach to questionnaires consists in measuring the performances of participants while they carry out ADL and IADL with the aid of sensor technologies allowing a non-invasive and continuous monitoring. Data gathered by the sensor technologies could allow for standardized quantitative and fully automated evaluation and contribute to the functional evaluation of a therapist.

A few studies using this newer evaluation approach have shown encouraging results in detecting MCI in older adults [8, 9, 13, 19, 1]. For example, Cook et al. [8, 19] used machine learning techniques to analyze behavior data of healthy older adults and adults with Parkinson's disease using wearable sensors. The authors found that differences between healthy older adults and adults with Parkinson's disease exist in their activity patterns, and that these differences can be automatically recognized. Dawadi et al. [9] used different machine learning algorithms namely principal component analysis, support vector machines, and logistic regression to quantify activity quality of healthy and cognitively impaired people in a smart home environment. The authors achieved reasonable results in differentiating between the two classes: healthy and cognitively impaired people. Jekel et al. [13] investigated smart home environment to assess ADLs for dementia diagnosis. Two groups of people: healthy and mild cognitive impairment were recruited to perform instrumental ADLs. Differences were observed for making a phone call, operating the television, and retrieving objects. The MCI group showed more searching and task-irrelevant behavior than healthy group. However, no machine learning algorithms were employed to differentiate between these two groups, and only statistical tests were used.

The main goal of the present study is to analyze smart home sensor data for automatic identification of behavioral patterns of people with mild cognitive impairments and Alzheimer's disease based on activities of daily living. Three groups of people were recruited in our study: healthy, MCI, and AD, which allows to collect rich data, and makes the identification of behavioral patterns more challenging. The contributions of the papers are summarized in the following points:

1. Identify automatically behavioral pattern of people with mild cognitive impairments and Alzheimer's disease using machine.
2. Perform experiments in two smart homes with different sensors types and setup to analyze ADLs and identify behavioral patterns.
3. Collect real data from three groups of participants: healthy, MCI, and AD.
4. Conduct extensive experimental tests to validate our proposed approach.

The rest of the paper is organized as follows. Section 2 introduces our proposed approach such as data collection procedures, dataset description, machine learning technique for data analysis and results obtained. Section 3 presents a comparison of our machine learning method with state-of-the-art methods. A discussion is presented in Section 4. Finally, Section 5 presents our conclusions and highlights future work directions.

2 Proposed approach

In this section, we describe our proposed approach for early detection of AD by analyzing sensor data collected during ADL's completion. Before introducing our approach, we will first describe the experimental setup in terms of participants and data collection procedures.

2.1 Participants

Two sites were used for recruiting participants: Sherbrooke and Montreal, Canada. A total of 56 participants (24 in Sherbrooke and 32 in Montreal) were recruited in this study. Details of participants and how they are recruited in the two sites are presented as follows:

Participants without cognitive impairment (n=26), control or healthy, were recruited in Sherbrooke and Montreal, mainly through databases of controlled participants. Inclusion criteria were: 1) to be 65 years of age or older; 2) to obtain normal results in cognitive disorders by age and education, as measured by the Montreal Cognitive Assessment (MoCA) [16]. Exclusion criteria were related to health conditions that could cause cognitive impairment: 1) History of cerebral involvement (head trauma, stroke, encephalopathy); 2) Uncontrolled diabetes or hypertension; 3) Presence of psychiatric disorders: schizophrenia, bipolar disorder, anxiety or depression; 4) delirium in the last six months; 5) Intracranial surgery; 6) Vitamin B12 deficiency or ethylism; 7) Use of medication that can influence cognition and alertness (hypnotics, neuroleptics, or anticonvulsants); 8) Physical impairments limiting the ability to move alone and safely in the intelligent apartment.

Participants with mild cognitive impairment (MCI) (n=22) were recruited via the Montreal Geriatric University Institute (IUGM) and the CSSS-Institute of Geriatric University of Sherbrooke (IUGS) via lists of participants. Inclusion criteria were: 1) to be 65 years of age or older; 2) have a diagnosis of MCI. This diagnosis was confirmed, in accordance with the current MCI criteria, [17, 24] by one of the two outpatient clinics, one at the IUGM institute and one at the IUGS institute. The exclusion criteria were the same as those of healthy participants.

2.2 Procedure

Participants were instructed to carry out five activities of daily living detailed on a sheet of paper.

Four of the selected activities[1] were validated in previous studies (Pigot et al. VOIR AVEC HLNE) and one (obtaining information on the phone) was based on the IADL Profile Bottari et al. [5]. Participants were asked to complete the five tasks in any order but within 45 minutes to increase the pressure, based on the procedure of the Six Elements Test of Shallice and Burgess [20]. Extension could be provided to allow for the completion of the tasks. The objective was

[1] Here we use the words "activity" and "task" interchangeably.

to highlight the planning and adaptation capacities to the novelty of the participants. Tasks were selected so that older adults without cognitive impairment should be able to perform all tasks without much difficulty, but that older adults with MCI or AD could experience difficulties in some tasks. Task 1: Place personal belongings (bag and coat) in the wardrobe; Task 2: Prepare a light meal (prepare an egg, two toasts with jam and a hot beverage with milk and sugar; set up the table; clean the tools); Task 3: Clean the bathroom (flush the toilet, wash the mirror and washbasin with a cleaner); Task 4: Telephoning for information on bus departures between Montreal and Toronto; Task 5: Answer the phone that will ring during the experiment and perform the task indicated by the caller, i.e. fold and store three pieces of clothing placed in the room. Each task took place at different room of the smart home.

Participants were free to choose the order and planning of tasks. The instruction sheet was available at all time so to allow compensation for participants with memory deficits. While performing the tasks, the experimenters were instructed to intervene as little as possible, but may intervene if he / she considers that a situation is unsafe, if the participant had been stuck on the same task for a long time, or if the participant hastily declares to be finished and did not attempt all tasks. If they were to intervene, they had to provide graduated indices in order to guide the participant as little as possible.

2.3 Datasets

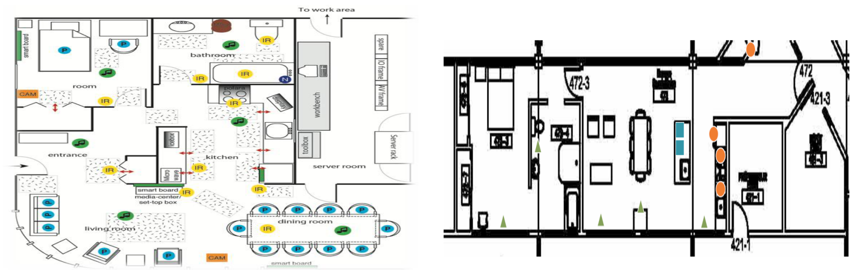
The data collected during experiments represent sensor data as shown in Table 1.

Table 1. Example of sensor data collected in a smart home at Sherbrooke.

Date	Time	Sensor Name	State / Value	Participant
2014-12-03	09:00:00	InfraRedSensor16	ON	MCI
2014-12-03	09:00:10	InfraRedSensor17	ON	MCI
2014-12-03	09:00:30	DoorSensor12	OPEN	MCI
2014-12-03	09:01:01	DoorSensor13	OPEN	MCI
2014-12-03	09:01:09	InfraRedSensor20	ON	MCI
2014-12-03	09:01:20	HotWaterSensor-B	ON	MCI
2014-12-03	09:01:50	ColdWaterSensor-A	ON	MCI

In Sherbrooke smart home, we count different types of sensors such as infrared sensors, contact sensors, pressure sensors, and debimeter sensors installed in different locations as shown in Figure 1(a). Whereas in Montreal smart home, we have three types of sensors: contact sensors, electric sensors and motion sensors as shown in Figure 1(b).

Sensors are triggered as participants perform ADLs. Therefore, it will be interesting to analyze sensor data in the order that sensors are triggered. The rational of analyzing data in this way is to have a clear idea about the progression of ADL's completion by participants and the possibility to intervene and assist participants in real time applications when help is needed or errors are detected.



(a) Sherbrooke smart home map (b) Montreal smart home map

Fig. 1. Sherbrooke and Montreal smart home maps and sensor locations.

The next section details our method for early detection of AD and MCI by analyzing data related to ADLs.

2.4 Proposed method

In this section, we present our proposed machine learning method for early detection of Alzheimer. We first present our feature selection method, followed by the learning and test method, and finally the results obtained. The steps of our method are presented in Figure 2. These steps are detailed in the following sections.

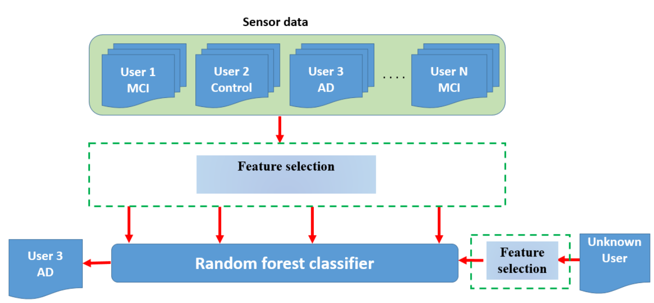


Fig. 2. The different steps of our method.

2.5 Feature selection

Feature selection is an important step in machine learning to build a good classification model. It allows to select best features for classification tasks. In addition, feature selection allows to reduce significantly the dimension of the data. For example, in the data collected in the smart home at Sherbrooke, we have

74 sensors. However, not all these sensors are useful and discriminant. Therefore, feature selection in this case is helpful to select only the most discriminant sensors that will help differentiate users.

We used different techniques to select the best features such as principal component analysis [22], Chi-square feature selection [14], and Latent semantic analysis method [15]. All these methods extract ten (10) common best features. Therefore, we reduced the dimensionality of data from 74 to 10, which will help reduce the computational complexity of the classification task. Once features are selected, we perform classification using random forests [7].

2.6 Classification

Several classification methods could be used such as SVM, decision trees, and naive Bayes to perform classification. We selected random forest classifier as it performed well in a wide range of classification tasks [10]. This motivates us to choose random forest to build our classification method. Random forest classifier operates by constructing several decision tree classifiers. The classification results of a random forest are obtained by majority voting over all decision trees. We experimentally setup the number of decision trees to 200 as this number achieves the best classification results compared to 10, 50, and 100 decision trees.

2.7 Leave One Out Cross Validation

We used leave one out cross validation method [23] to evaluate our method. We performed cross validation on data collected at Montreal and Sherbrooke smart homes separately. For example, for data collected at Sherbrooke smart home, we used all data from 23 participants for training and the data of the remaining participant for testing. We performed the experiment 24 times, excluding one participant at each time. We performed the same experiments with data collected from Montreal smart home with 32 participants. The benefit of such setup is twofold. First, it allows detecting problematic participants and analyzing the sources of some of the classification errors caused by these participants. A problematic participant means his/her activities were performed differently compared to other participants. Second, it allows testing the inter-participant generalization of the method, which constitutes a good indicator about the practicability of our method. Tables 2 and 3 show the classification results obtained for each participant using the F-score measure. Note that the F-score is calculated as follows: $F - score = \frac{2\times(precision\times recall)}{precision+recall}$.

Table 2. Classification results obtained using data collected in Sherbrooke smart home.

User	Type	F-score	User	Type	F-score	User	Type	F-score
1	Control	0.886	11	MCI	0.819	21	AD	0.984
2	Control	0.918	12	MCI	0.316	22	AD	0
3	Control	0.934	13	MCI	1	23	AD	0.91
4	Control	0.938	14	MCI	0.484	24	AD	0.976
5	Control	0.965	15	MCI	1			
6	Control	0.903	16	MCI	0.537			
7	Control	0.907	17	MCI	0			
8	Control	0.911	18	MCI	1			
9	Control	0.934	19	MCI	0.468			
10	Control	0.96	20	MCI	0.515			

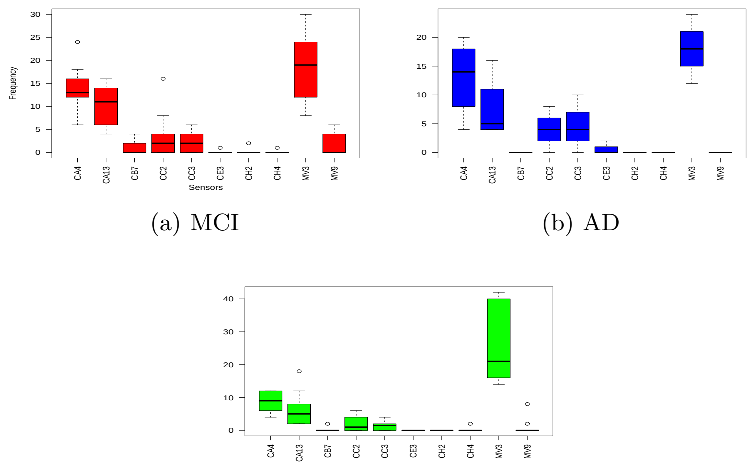
Table 3. Classification results obtained using data collected in Montreal smart home.

User	Type	F-score	User	Type	F-score	User	Type	F-score
1	Control	0.933	12	Control	0.625	23	MCI	0.667
2	Control	0.8	13	Control	0.947	24	MCI	0.462
3	Control	0.917	14	Control	0.909	25	MCI	0
4	Control	0.917	15	Control	0.8	26	MCI	0
5	Control	0.947	16	Control	0.609	27	MCI	0.4
6	Control	0.857	17	MCI	0	28	MCI	0.222
7	Control	0.615	18	MCI	0.533	29	AD	0.455
8	Control	0.615	19	MCI	0.667	30	AD	0.667
9	Control	0.667	20	MCI	0.154	31	AD	0.72
10	Control	0.609	21	MCI	0.375	32	AD	0
11	Control	0.615	22	MCI	0.235			

As shown in Table 2, in Sherbrooke smart home, our method is able to differentiate between the three categories of people control, MCI and AD with an average F-score = 0.761, which is promising given the small number of participants with AD (4 participants). Note that our method identifies perfectly participants with AD as demonstrated by the high values of the F-score except for one user (User 22 in Table 2) incorrectly classified as participants with MCI. This means that User 22 performs activities in the same way participants with MCI do. Similarly, participant User 17 (MCI) was incorrectly classified as participants with AD. These findings may help identify patients with MCI who are more likely to develop AD given the level of difficulty they experience during the realization of ADLs. The same observation applies for the patient with AD that performs better in realizing activities of daily living compared to the three other patients with AD. Finally, our method is able to identify perfectly control participants as shown in Table 2. The same observation applies for participants with AD except for User 22.

However, the classification results obtained using data collected from Montreal smart home are not very promising since the average F-score is 0.56, which is slightly better than a random classifier. This can be explained by the small number of wireless sensors used to collect data, which is not enough to differentiate between participants. One important observation here is that all MCI and AD participants with F-score null in Table 3 are incorrectly classified as control participants. Consequently, Users 17, 25, 26 and 32 perform activities similarly to control participants.

Note that each category of participants performs activities differently. This can be shown by the number of times sensors are triggered for each category of participants for all activities using data from Sherbrooke smart home. Figure 3 shows the number of times sensors are triggered when participants in each category perform ADLs in Sherbrooke smart home.



(a) MCI (b) AD

(c) Control

Fig. 3. Number of times sensors triggered for each category of participants.

As shown in Figure 3, sensors are triggered more frequently in MCI and AD categories compared to control category. For example, sensor CA4 (contact sensor) has been triggered around 20 times for the categories MCI and AD as shown in Figures 3(a) and 3(b), while it has been triggered around 10 times for control participants as shown in Figure 3(c). This can be explained by the fact that control participants find easily utensils and objects used to perform activities compared to the other two categories where participants tried to look for objects everywhere and open different cabinets and drawers to find objects. The same observation applies to the other sensors except for sensor MV3 (movement sensor) that has been triggered more frequently, between 20 and 40 for control participants as shown in Figure 3(c) compared to the other two categories where it has been triggered between 15 and 25 times. This can be explained by the fact that MCI and AD participants wait for help when they were unable to perform activities, compared to control participants who continue performing activities.

We performed other experiments by merging the two categories MCI and AD. Our goal is to identify abnormal realization of ADLs. The advantage of this method is to quickly distinguish between normal participants (control) and participants with cognitive deficits. Tables 4 and 5 show the recognition results for both categories in Sherbrooke and Montreal smart homes respectively.

Table 4. Classification results obtained using data collected at Sherbrooke smart home using two categories of participants.

User	Type	F-score	User	Type	F-score	User	Type	F-score
1	Control	0.986	11	MCI-AD	1	21	MCI-AD	1
2	Control	0.947	12	MCI-AD	0.43	22	MCI-AD	1
3	Control	0.935	13	MCI-AD	1	23	MCI-AD	1
4	Control	0.96	14	MCI-AD	0.203	24	MCI-AD	1
5	Control	0.934	15	MCI-AD	1			
6	Control	0.96	16	MCI-AD	0.795			
7	Control	0.964	17	MCI-AD	0.991			
8	Control	0.921	18	MCI-AD	1			
9	Control	0.995	19	MCI-AD	0.846			
10	Control	1	20	MCI-AD	0.523			

Table 5. Classification results obtained using data collected at Montreal smart home using two categories of participants.

User	Type	F-score	User	Type	F-score	User	Type	F-score
1	Control	0.857	12	Control	0.533	23	MCI-AD	0.667
2	Control	0.8	13	Control	0.947	24	MCI-AD	0.182
3	Control	0.917	14	Control	0.909	25	MCI-AD	0.667
4	Control	0.87	15	Control	0.759	26	MCI-AD	0.667
5	Control	1	16	Control	0.476	27	MCI-AD	0.4
6	Control	0.897	17	MCI-AD	0	28	MCI-AD	0.222
7	Control	0.87	18	MCI-AD	0.625	29	MCI-AD	0.583
8	Control	0.615	19	MCI-AD	0.571	30	MCI-AD	0.857
9	Control	0.333	20	MCI-AD	0	31	MCI-AD	0.769
10	Control	0.545	21	MCI-AD	0.632	32	MCI-AD	0.4
11	Control	0.615	22	MCI-AD	0.333			

As shown in Table 4, our method differentiates perfectly between healthy participants (control) and participants with cognitive deficits (MCI and AD) in the Sherbrooke smart home with an average F-score of 0.891. We can see that User 14 is identified as participants with MCI-AD with an F-score of only 0.203. This means that this participant performed activities similarly to normal participants compared to other participants with MCI-AD. The same observation applies for User 12 with an F-score of 0.43. These observations are of great importance since they allow to identify persons with cognitive deficits who are still able to perform ADLs correctly. This will help them to stay engaged in realizing activities, which may allow to delay their cognitive decline. However, as shown in Table 5, our method did not perform perfectly with data collected in Montreal smart home. This was expected for two main reasons 1) the small number of sensors used, which creates more confusion between participants, and 2) all MCI and AD participants incorrectly classified by our method were classified as control participants this means that merging the MCI and AD categories does not help in differentiating between healthy participants and those with cognitive deficits. The results obtained using data from Montreal smart home suggest that using small number of sensors is not suitable for detecting patients with cognitive deficits or recognizing their activities of daily living. The use of very small number of sensors may create more confusion between participants, and make the task of detecting participants with cognitive deficits more complicated.

3 Comparison

We compared our method with several state-of-the-art machine learning algorithms such as support vector machines (SVM), Hidden Markov Models (HMM), Bayesian networks (BN), Naive Bayes (NB), decision trees (DT), K Nearest Neighbors (KNN), and multilayer perceptron neural network(mlp). Table 6 shows the comparison results obtained for all methods in terms F-score in both scenarios, i.e. with three categories of participants and two categories respectively using data from Sherbrooke smart home.

Table 6. Comparison results between our method and state-of-the-art- methods using data collected in Sherbrooke smart home.

	Three categories Control, MCI, AD	Two categories Control, MCI-AD
Method	F-score	F-score
Our method	**0.761**	**0.891**
SVM	0.727	0.822
HMM	0.5	0.655
BN	0.703	0.804
NB	0.71	0.807
DT	0.722	0.817
KNN	0.722	0.809
MLP	0.709	0.787

As shown in Table 6, our method outperforms all the state-of-the-art machine learning classifiers for both scenarios (three categories of participants and two categories). The HMM models performs poorly in both scenarios. This can be explained by the small sample size of the data as HMM models require more training data to perform well. The SVM model performs well also in both scenarios compared to the other classifiers.

4 Discussion and Conclusion

In this paper we proposed a method for automatic detection of patients with Alzheimer's based on activities of daily living. We collected real data related to five activities of daily living from fifty-six (56) participants to perform experiments in two different smart homes. We performed feature selection in order to identify the most discriminant features and reduce the dimensionality of the data. The selected features were then fed into a random forest classifier for learning and testing. With a leave one out cross validation method, we were able to identify the three categories of participants (control, MCI and AD) with an average F-score of 0.76 and 0.56 using data collected in Sherbrooke and Montreal smart homes respectively, which is very promising given the small sample of participants with AD. We also empirically demonstrated that our proposed method is suitable in differentiating between healthy participants (control) and participants with cognitive deficits (MCI and AD) with an average F-score of 0.89 and 0.60 using data collected in Sherbrooke and Montreal smart homes respectively. We were able to extract problematic participants who perform activities of daily living differently than the other participants of the same category.

The novel aspect of our research is to evaluate dysfunctions in ADL in normal aging, MCI and dementia conditions on a continuum of ability using a new performance-based approach, using simple sensors but most importantly, efficient machine learning approaches.

The experiments performed in this work suggest that the use of a small number of sensors may create confusion between participants and make the identification of participants more challenging and complicate. This is demonstrated by the results obtained using the two smart home data. Indeed, at Sherbrooke smart home, where the relatively large number of sensors allows to create a profile for each category of participants that helps identify participants of each category. In contrast, the small number of sensors used in Montreal smart home demonstrates the limitation in identifying participants of each category. Consequently, using more sensors allows to capture more variations in activities of daily living, which helps discriminating between participants.

In conclusion, we hypothesized that this method of evaluation may support currently used tools. Future study in the field may contribute to better early detection of dementia and identification of the persons difficulties and needs, which in turn will lead to more tailored interventions.

References

1. A. Akl, B. Chikhaoui, N. Mattek, J. Kaye, D. Austin, and A. Mihailidis. Clustering Home Activity Distributions for Automatic Detection of Mild Cognitive Impairment in Older Adults. *J Ambient Intell Smart Environ*, 8(4):437–451, 2016.
2. Fabrigoule C. Helmer C. Rouch-I. Dartigues J.F. Barberger-Gateau, P. Functional impairment in instrumental activities of daily living: an early clinical sign of dementia? *Journal of the American Geriatrics Society*, 47(4):456–462, 1999.
3. Rainville C. Letenneur L. Dartigues-J.-F Barberger-Gateau, P. A hierarchical model of domains of disablement in the elderly: a longitudinal approach. *Disability and Rehabilitation*, 22(7):308–317, 2000.
4. Letenneur L. Barberger-Gateau P., Dartigues J.F. Four instrumental activities of daily living score as a predictor of one-year incident dementia. *Age and Ageing*, 22(6):457–463, 1993.
5. C. Bottari, C. Dassa, C. Rainville, and E. Dutil. A generalizability study of the instrumental activities of daily living profile. *Arch Phys Med Rehabil*, 91(5):734–42, 2010.
6. Dutil E. Dassa C. Bottari, C. and C. Rainville. Choosing the most appropriate environment to evaluate independence in everyday activities: Home or clinic? *Australian Occupational Therapy Journal*, 53:98–106, 2006.
7. Leo Breiman. Random forests. *Mach. Learn.*, 45(1):5–32, October 2001.
8. Dawadi P Cook DJ, Schmitter-Edgecombe M. Analyzing activity behavior and movement in a naturalistic environment using smart home techniques. *IEEE J Biomed Health Inform*, 19(6):1882–92, 2015.

9. P. N. Dawadi, D. J. Cook, M. Schmitter-Edgecombe, and C. Parsey. Automated assessment of cognitive health using smart home technologies. *Technol Health Care*, 21(4):323–343, 2013.
10. Ramón Díaz-Uriarte and Sara Alvarez de Andrés. Gene selection and classification of microarray data using random forest. *BMC Bioinformatics*, 7(1):7:3, Jan 2006.
11. Koppel J. Keehlisen L. Christen E.-Dreses-Werringloer U. Conejero-Goldberg C. et al. Goldberg, T.E. Performance-based measures of everyday function in mild cognitive impairment. *Am J Geriatr Psychiatry*, 167(7):845–853, 2010.
12. Byerly L.K. Vanderhill S. Lambe S.-Wong-S. Ozonoff A.-et al. Jefferson, A.L. Characterization of activities of daily living in individuals with mild cognitive impairment. *Am J Geriatr Psychiatry*, 16(5):375–383, 2008.
13. K. Jekel, M. Damian, H. Storf, L. Hausner, and L. Frolich. Development of a Proxy-Free Objective Assessment Tool of Instrumental Activities of Daily Living in Mild Cognitive Impairment Using Smart Home Technologies. *J. Alzheimers Dis.*, 52(2):509–517, 2016.
14. Xin Jin, Anbang Xu, Rongfang Bie, and Ping Guo. Machine learning techniques and chi-square feature selection for cancer classification using sage gene expression profiles. In Jinyan Li, Qiang Yang, and Ah-Hwee Tan, editors, *Data Mining for Biomedical Applications*, pages 106–115, 2006.
15. Tao Liu, Zheng Chen, Benyu Zhang, Wei ying Ma, and Gongyi Wu. Improving text classification using local latent semantic indexing. In *Data Mining, 2004. ICDM '04. Fourth IEEE International Conference on*, pages 162–169, 2004.
16. Bdirian V Charbonneau S-Whitehead V Collin I-Cummings J.L Chertkow H Nasreddine Z.S, Phillips N.A. The montreal cognitive assessment, moca: a brief screening tool for mild cognitive impairment. *Journal of the American Geriatrics Society*, 53(4):695:699, 2005.
17. R. C. Petersen. Mild cognitive impairment as a diagnostic entity. *Journal of Internal Medicine*, 256(3):183–194, 2004.
18. Amieva H Orgogozo J-M Rouch I Dartigues J-F Barberger-Gateau P. Prs K, Helmer C. Natural history of decline in instrumental activities of daily living performance over the 10 years preceding the clinical diagnosis of dementia: A prospective population-based study. *Journal of the American Geriatrics Society*, 56(1):37–44, 2008.
19. A. M. Seelye, M. Schmitter-Edgecombe, D. J. Cook, and A. Crandall. Naturalistic assessment of everyday activities and prompting technologies in mild cognitive impairment. *J Int Neuropsychol Soc*, 19(4):442–452, Apr 2013.
20. Tim Shallice and Paul W. Burgess. Deficits in strategy application following frontal lobe damage in man. *Brain*, 114(2):727–741, 1991.
21. Visser P.J. Knol D.L. de Lange-de Klerk E.S.M. Tsolaki M.-Frisoni G.B.-et al. Sikkes, S.A.M. Do instrumental activities of daily living predict dementia at 1- and 2-year follow-up? findings from the development of screening guidelines and diagnostic criteria for predementia alzheimer's disease study. *Journal of the American Geriatrics Society*, 59(12):2273–2281, 2011.
22. F. Song, Z. Guo, and D. Mei. Feature selection using principal component analysis. In *2010 International Conference on System Science, Engineering Design and Manufacturing Informatization*, volume 1, pages 27–30, 2010.
23. Aki Vehtari, Andrew Gelman, and Jonah Gabry. Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and Computing*, 27(5):1413–1432, September 2017.

24. Kivipelto M Jelic V-Fratiglioni L Wahlund L.O Nordberg A Bckman L Albert M Almkvist O Arai H Basun H Blennow K de Leon M DeCarli C Erkinjuntti T Giacobini E Graff C Hardy J Jack C Jorm A Ritchie K van Duijn C Visser P Petersen R.C. Winblad B, Palmer K. Mild cognitive impairment–beyond controversies, towards a consensus: report of the international working group on mild cognitive impairment. *Journal of Internal Medicine*, 256(3)::240–6, 2004.